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Detection and Characterization of Oil Palm Plantations through MODIS EVI Time Series

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Oil palm is a perennial tree that well fits the humid tropical climate; fresh fruit bunches (FFB) are the palm raw fruit for oil mills. Palm oil is the world highest yielding oil crop determining that palms are extensively planted in South-East Asia, especially in Malaysia, Thailand, and Indonesia where plantations have been spreading in response of the increasing market demand. Cultivation of oil palm in tropical countries is an important economic factor, but, it has already proved of endangering biodiversity and degrading environment with a global impact related to forest loss. Remote sensing well fits requirements of precision farming that many stakeholders involved in palm oil production are currently approaching to decrease or monitor environmental impacts. In this work, an EVI (Enhanced Vegetation Index) time series of 415 images was obtained from the MODIS Vegetation Index 16 days composite product (MOD13Q1-v5) to explore tropical vegetation changes. The EVI time series covers a period of 18 years; it was processed aiming at mapping new oil palm plantations in the reference period, giving an estimate of their age, production and economic value. In this work, a new methodology for oil palm detection and characterization was presented based on local EVI temporal profile analysis. Pixel EVI temporal profile proved to be effective in describing both vegetation macro-phenology and forest loss at that position. Consequently, the proposed algorithm looks for abrupt changes along the local EVI time series (sudden decreasing). The minimum EVI value recorded in the detected changing period is assumed as predictor of the starting date of new plantations, being the latter reasonably related to forest loss and preliminary soil preparation. Starting date is then used by algorithm to estimate oil palm age and, consequently, the present local (potential) production.

Accuracy assessment showed an overall accuracy in new palm oil plantations detection of about 94%. Starting age estimation proved to be accurate enough: 76% of estimates, in fact, were placed in a range of uncertainty of 1 year.

Keywords: Oil Palm, MODIS, EVI, Time Series Analysis, Plantation Age, Palm production, FFB, Palm Detection, Borneo.

1. Introduction

Palm oil is the world highest yielding oil crop. The consumption of palm oil over the world is growing through the years: 55 Million tons in 2012-2013, over 60 Million tons in 2015-2016 (Chong 2017). According to FAO (FAO 2018), presently, the two largest palm oil producing countries are Indonesia and Malaysia. *Elaeis guineensis* Jacq. is a palm species of the *Arecaceae's* family commonly called Oil palm; it is planted extensively in South-East Asia, especially in Malaysia, Thailand, and Indonesia. In Indonesia plantations showed an increasing linear trend that brought the 4 million hectares in 2000 up to 11 million hectares in 2015 (Chong 2017). Oil palm is a perennial tree that well fits the humid tropical climate (high precipitation rate, high solar radiation and warm temperature between 24–32 °C (Corley and Tinker 2008). Oil palm plantations, generally, have a triangular pattern (9 m row spacing), to optimize sunlight penetration (Basiron 2007). The majority of planted oil palms are a small mixture of hybrid clones, i.e. Dura x Pisifera, (Chong 2017), resulting in a uniform pattern at the ground; this makes oil palms different from other trees or forest in satellite imagery (Shafri et al. 2011). Cultivation of oil palm in tropical countries is an important economic factor, but, it greatly endangers biodiversity and degrades the environment with a global impact (Koh and Wilcove 2008). In these regions, in fact, the last world tropical forests are present (Iremonger et al. 1997), containing numerous endemic or rare species, many of which are restricted to forest habitats (Mittermeier et al. 2004; Sodhi et al. 2004; Koh 2007). Over-logged forests are often considered as degraded habitats by governments, just waiting for conversion to agriculture. This fact, has encouraged the transformation of secondary (logged) forests to oil palm plantations in Malaysia and Indonesia (McMorrow and Talip 2001). From this point of view remote sensing can support a more efficient plantation strategy that takes into account environmental/ecological instances. Moreover, plantations monitoring by remote sensing well fits requirements of precision farming that many stakeholders are currently approaching to decrease environmental impacts of their practices. Private owners and local farmers are, in fact, interested in assessing crop conditions along its growing season; differently, governmental institutions and environmental associations long for the possibility of continuously monitoring the state of the national natural/crop capital. Among the available remotely sensed data, the NASA's sensors MODerate resolution Imaging Spectroradiometer (MODIS) onboard the Terra and Aqua satellites have been widely used in a variety of studies (Testa et al. 2018; Colombo et al. 2011; Hmimina et al. 2013; Soudani et al. 2008; Zhang et al. 2003). Thanks to the two twin MODIS instruments, MODIS data are acquired globally averagely twice per day per instrument at the spatial resolutions of 250 m, 500 m and 1 km at nadir, depending on the considered spectral band. MODIS imagery is distributed at various pre-processing levels and, with respect to the temporal resolution, data are released as both daily and composites products, the latter generated at different compositing steps (8-day, 16-day, monthly). Composite data have some advantages in respect of daily data, since the compositing process strongly reduces cloud, snow and sensor noise effects (Solano et al. 2010). In this work a time series of EVI (Enhanced Vegetation Index, Huete et al. 1999) maps, covering the period 2000–2018, was generated from the MODIS Vegetation Index products (MOD13Q1-v5) with the aim of automatically detecting new oil palm plantations and possibly giving an estimate of their age, production and economic value. EVI spectral index has proved to be more effective in mapping vegetation in those situations where atmospheric scattering and vegetation vigor are high, and background contribution to signal is not negligible (Hufkens et al. 2012; Xiao et al. 2003). These are exactly the conditions that can be found in the Borneo area, therefore suggesting the adoption of EVI in place of the ordinary NDVI (Normalized Difference Vegetation Index). It is worth to remind at this point, in this work authors, while mapping oil palm plantations, voluntarily did not refer to any of locally available data to test accuracy of deductions. One of requirements of this work was, in fact, to "objectively" map plantations in spite of any official existing data. This was mandatory since the method was intended to define a procedure to control the reliability of farmers/company communications about the size and position of their plantations to National Institutions. Consequently, only external data and self-conducted photointerpretations from available high resolution satellite images were taken into account to test accuracy of deductions.

2. Materials and Methods

2.1 Study Area

The study area is located in the South of Kalimantan Tengah (Central Kalimantan), a province of Indonesia belonging to the Borneo island (2°53'57.58"S - 112°22'6.47"E , WGS-84 reference frame). It was selected as representative of a wider area having similar features, based on landscape markers criteria (rivers, coast, etc.), resulting in about 2.95 million hectares (Fig. 1). According to Köppen classification, local climate is considered tropical rainforest. It is dominated by low-pressure system all over the year generating no thermal and moisture seasonality. According to USDA (United States Department of Agriculture) Soil Taxonomy, local soil is mainly labelled as *Oxisol* with a high aluminium and low phosphate content that could hinder plant growth. Morphology is generally flat without significant reliefs, even if some local microsites conditions could affect vegetative vigour of plantation. Nevertheless, edaphic conditions of area can be retained constant at the small scale.

[Figure 1]

2.2 Available Data

An EVI (Enhanced Vegetation Index) image time series (hereinafter called ETS), composed of 415 images covering the period 18/02/2000 - 18/02/2018, was generated from the MOD13Q1-v5 dataset available from the NASA LPDAAC collection (Solano et al. 2010). According to Huete (1999) EVI is a vegetation index designed to enhance vegetation signal in high biomass regions (like equatorial rainforest) improving monitoring through a de-coupling of the background signal and a reduction of the atmosphere influence. EVI is computed according to Equation (1):

$$EVI = \frac{G\ (\rho NIR - \rho RED)}{(\rho NIR + C1\ \rho RED - C2\ \rho BLUE + L)} \quad (1)$$

where ρ are at-the-ground reflectances, L is the canopy background adjustment that addresses nonlinear, differential NIR and red radiant transfer through a canopy, and C1, C2 are the coefficients of the aerosol resistance term, which uses the blue band to correct aerosol influences in the red band. The coefficients adopted in the EVI algorithm are, L = 1, C1 = 6, C2 = 7.5, and G (gain factor) = 2.5. As reference data to validate results from ETS processing, the Global Forest Change (GFC) 2000-2016 dataset-v1.4 (Hansen et al. 2013) was obtained from the

Hansen/UMD/Google/USGS/NASA system in raster format. GFC is divided into 10 x 10 degree tiles, consisting of seven files per tile. All files are unsigned 8-bit having a spatial resolution of 1 arc-second per pixel (approximately 30 meters per pixel at the equator). Year of gross forest cover loss event grid (*lossyear*, hereinafter called GFC-YL) is defined as a disaggregation of total forest loss to annual time scales. In this dataset, zero values mean “no forest loss”, values in the range 1–16 (2000-2016) indicate the year when a forest loss detection occurred. For this work, starting from native GFC-YL, a new forest cover loss 2000–2016 (hereinafter called GFC-L) layer was generated representing forest losses in the period 2000–2016, defined as both stand-replacement disturbance, or changes from a forest to non-forest state. In GFC-L pixels where forest loss was detected are coded as 1, while the others were set to 0. Both the GCF raster layers were preventively projected into the WGS84 UTM 49 S reference system, setting a Ground Sampling Distance (GSD) of 250 m. Image processing for oil palm plantations detection was achieved by a self-developed routine implemented in IDL 8.0 programming language. Results and intermediate steps were managed by free GIS software (QGIS 2.18.4 and Saga GIS 6.2).

2.3 Mapping new oil palm plantations

A new methodology for oil palm detection and characterization was developed and implemented based on temporal profile analysis of each ETS pixel. EVI temporal profile proved to be effective in describing dynamics of vegetation cover with particular concern on its macro-phenology. The detection algorithm analyzes local ETS profile looking for an abrupt change in EVI values (sudden decreasing) along the considered period (18 years). Candidate pixels, possibly representing new oil palm plantations, were detected with reference to the 1st order polynomial (eq. 2) approximating EVI local time profile in the whole reference period; the estimated gain value of the computed regression line was assumed as predictor of new oil palm plantations and saved in a new image layer, hereinafter called **G(x,y)**.

$$EVI(DOY) = G(x,y) \cdot DOY + O(x,y) \quad (2)$$

where DOY is the generic Day of the Year, G(x,y) and O(x,y) the estimated gain and offset values at that position in the image (ETS).

Theoretical assumption was that, in tropical areas, new oil palm plantations show a gain higher than natural vegetation, being the EVI values of the new cover significantly higher than the one ordinarily expressed by natural vegetation. The ideal EVI temporal profile of pixels interested by new plantations shows three periods of interest (Fig. 2).

[Figure 2]

In the first period (A), previously existing forest cover (natural or semi-natural vegetation like forest or secondary logged forest) is still present. In phase B, a sudden EVI decreasing indicates that a land cover change is taking place, probably related to the combined effect of pre-existing vegetation cut and consequent soil preparation activities, preceding palm seedlings planting. The point when the minimum value of the local ETS profile could be found, was assumed as the new plantation starting moment (see forward on and Fig. 2). The C phase is the one when new planted palms begin to improve their biomass and grow, determining a progressive increase of EVI values. The final (mature) stage of palm growing corresponds to a new higher plateau in ETS. This determines that, in this condition, the overall regression line shows higher and positive gain values than those that a persisting forest cover would have showed. In general, can be observed that when natural vegetation is constantly present, yearly EVI trend is slightly varying with no remarkable profile steep trait, determining gain values of regression line close to zero. Differently, if a new plantation occurs, EVI temporal profiles suddenly decreases at the moment of forest cut, but, after a transitional period, it reaches a new state of vigor corresponding to higher EVI values. The above mentioned succession well fits the ordinary practice for oil palm plantations, that mainly follows 3 steps (Carlson 2012): I) Forest or previous vegetation cutting; II) area burning (fires are considered to be a cheap and effective method to clear and maintain land for agricultural and plantation development (Marlier 2015); III) soil preparation and new seedlings planting. The abrupt EVI value decreasing that occurs when natural vegetation is cut, the consequent oil palm planting and growing determines a significant increasing of line gain, in general higher than 2.0. This reference value was found exploring the behaviour of 200 control points (CPs) testing in the area locations with and without oil palms. CPs were obtained by photointerpretation of 2 available Sentinel-2 RGB true color composites (R: band 4, G: band 3; B: band 2) from the T49MFS and T49MFT tiles, respectively acquired on 2018/02/08 and 2018/02/13; 100 CPs were placed in evident OP areas and 100 in NOP ones (Fig. 3). The local value of G(x,y) was therefore extracted for each CP, determining two groups (OP and NOP) of G values. To test their a-priori separability a Jeffries-Matusita test (Richards and Richards, 1999) was achieved. To select a proper threshold for G, the mean (μ) and the standard deviation (σ) values of G were computed for NOP points.

[Figure 3]

To map ETS pixels that potentially suffered from changes from natural vegetation to oil palm in the reference period, **G(x,y)** was thresholded to separate potential oil palm (OP, **G(x,y)** ≥ 2.0) pixels from the others (NOP, **G(x,y)** < 2.0), obtaining a rough map of potential new oil palm plantations (Fig. 6a and 6b) with the following codes: 1= Oil Palm (OP), 0 = Not-OP (NOP). Raster classification was vectorised and refined deleting (by ordinary GIS vector map editing tools) all those polygons smaller than 100 ha, being declared plantation average size in general higher of this value, typically following a rectangular pattern of 1000 m x 300 m (Fig. 4).

[Figure 4 in the text, on the left]

2.4 Estimating Starting Date and Age of Plantations

The age of oil palm plantation is an important parameter for crop management: it is a good predictor of yearly yield and conditions the quality and quantity of the *fresh fruit bunches* (FFB). According to the above mentioned classification, ETS profile of all the OP pixel were analyzed at year level looking for the moment of the vegetation loss preceding oil palms plantation. The minimum EVI value along the local ETS was assumed as predictor for new plantations starting date. Unfortunately, many outliers along ETS made not possible to operate on the raw ETS, making desirable a preliminary ETS filtering aimed at minimizing effects of local EVI anomalous variations (Fig. 7). Filtering was achieved by a "customized" low pass filter having a kernel size of 15 observations (7 preceding and 7 following the central one) running along ETS. The size of the kernel was set according to the expected detectable phenology of oil palm from ETS as reported in Lam Kuok Choy (2016), where about 6-7 months seem to represent the lasting of the "low vigour" phase of oil palm phenology. In this period sudden EVI variations could be reasonably related to anomalous values to be smoothed.

Filter was applied selectively according to the difference between the EVI center value of the sliding window and its estimate from the local regression line. If difference was larger than 0.15 points of EVI filter was applied, otherwise it was not. The threshold of 0.15 was selected in respect of repeated visual interpretation of reference EVI profiles randomly sampled from the image. Selective smoothing permitted to cut off short-term ETS fluctuations, enhancing long-term ones. With respect to the filtered ETS, for each

OP pixel, the minimum EVI value was found and the correspondent year number saved in a new image layer (Fig. 8b). A new raster map was therefore generated representing, in the space domain, the time distribution of new plantations. The age of plantations was consequently computed at each position by differencing the estimated planting year with present (2018, Fig. 8a). This method proved to be able to detect the moment when extensively soil practices occurred (period III) making possible to overcome the uncertainty related to land cover changes possibly due to other reasons (agroforestry, forest logging, natural disturbances, etc,). In fact, many methods based on remotely sensed data are able to detect stand replacing disturbances resulting by land cover change (e.g. forest logging, period I) without making distinctions or explicit which step of land cover transition they detect. Analyzing some representative oil palm ETS pixel we found that the land cover transition, in general, proceeds on for more than one year before reaching the EVI minimum value determining a time lag between forest cut and plantation of new oil palm seedlings. For this reason, authors took into account only the period III as plantation starting moment and consequently it was used to calculate the strongly related age of plantation.

2.5 Estimating oil palm production

Oil palms produce FFB that represent the raw material for palm oil mills. Oil is extracted from the pulp of the fruit or from the kernel. Production can be affected by various internal and external factors. Internal factors include age and oil palm breeds/variety; external factors include rainfall, drought, disease, soil fertility and moisture, harvesting efficiency (Chong 2017). Thus, to give an estimate of production, all the above mentioned factors would have to be taken into consideration. Nevertheless, a good synthetic predictor of yield is the age of plantation itself. The relationship of yield of oil palm and age establishes a sigmoid shape, fitting a nonlinear regression growth model across its life cycle (Khamiz et al. 2005). Thus, by retrieving the age information of oil palms and the total planted area using remote sensing, the total FFB production of the mentioned area can be roughly estimated using a regression model (Khamiz et al. 2005). Ismail and his collaborators (2002) proposed a time dependent unitary production (UP) curve for oil palm (Fig. 5), relating FFB yearly yield (tons FFB ha^{-1} yr^{-1}) with the age of plantation (annual basis). Consequently, authors used it as a look up table relating the estimated age of plantation to the expected UP in 2018. To give an estimation of local production (LP) UP was multiplied by the area of each MOD13Q1 pixel. A map of expected LP was, therefore, generated for the year 2018 (Fig. 10a).

[Figure 5]

2.6 Economic value of oil palm plantations

According to FAO dataset (FAO 2018), Indonesia FFB annual producer price (US Dollar $tonFFB^{-1}$), in refers to 2016, is 111 US Dollar $tonFFB^{-1}$. Later reference time (2017-2018) there are not available, nevertheless, actually FAO data is the most reliable data about FFB price. Therefore, a new estimate production map was generated. Multiplication between FFB annual producer price and LP until 2018 a new plantation economic value map (Fig. 10b) was generated and summarized in table 1. Total economic value of whole study area, in refers to 2018 yield and using 2016 FAO producer price, is about 1.2 Billions USD.

3. Results and Discussion

In respect of the above mentioned procedure, oil palm plantations mapping was achieved computing the 1st order polynomial approximating EVI local time profile in the whole reference period and mapping the correspondent gain value, G(x,y). OP were detected by thresholding G(x,y). According to the previously mentioned statistical analysis, the selected threshold to separate OP from NOP pixels was set to 2.0.

The Jeffries-Matusita (JM) test was successful, indicating that OP and NOP control points were statistically separable. The JM score was, in fact, 1.93. Concerning G(x,y) threshold selection, the mean (μ) and standard deviation (σ) values of G were computed for NOP points. NOP μ and σ resulted respectively 0.109 and 0.913. Considering a confidence interval of 95 % , corresponding to $\mu+2\sigma = 1.935$, we admitted that OP pixels could be identified looking for local G values higher than this number. Consequently, a threshold value of 2.0 was selected for G(x,y) to separate OP from NOP pixels. OP detection results are shown in maps of figure 6.

[Figure 6]

Classification accuracy assessment was achieved with reference to GFC-L. Refined vector map was converted back to the raster format by nearest neighbour resampling, making it consistent with GCF-L (GSD = 250 m). It is worth to remind that GFC-L represents the forest loss occurred in the period 2000-2016, that authors assumed to be potentially and totally due to new oil palm plantations in the same period. In fact, in this region new palm plantations are the first reason of forest loss (Curran 2004), making this assumption reasonable. Concerning new oil palm plantation detection the proposed method, based on the thresholding of the gain value of the regression line computed along the whole ETS, proved to be effective: overall accuracy was found to be equal to 94%. In the area about 545394 ha (18.5% of the whole study area) were converted from forest to oil palm plantations in the reference period (2000-2018). Gain value of the line interpolating the entire ETS at pixel level proved to be a good discriminant to map vegetation changes and, in particular, those where the following succession occurred: forest vegetation-cutting-oil palm plantation. In fact, replacement of forest with other surface types (e.g. urban or bare soil) would have determined lower, possibly negative, values of gain and not highly positive as the threshold value proposed in this work. Concerning plantations age estimates the maps of figure 8 were produced according to the proposed method, after selective filtering of the local EVI temporal profiles of OP pixels (an example of EVI profile for a generic OP pixel is reported in figure 7).

[Figure 7]

[Figure 8]

Estimation of plantations age proved to be more critical; transition matrix was calculated by difference between map of plantations age estimates and GCF-YL. Correspondent cumulative frequency distribution of absolute differences is reported in figure 9. It shows that only 47% of detected plantations present differences equal to 0, i.e. correctly dated. Nevertheless, it must be considered that the proposed method gives an estimate of the moment when soil preparation/new seedlings occurred. Differently, the reference dataset (GCF-LY), maps the moment of forest loss determining a time lag between the two estimates. Considering that a time delay of one year between previous vegetation cutting and planting of new oil palm seedlings is reasonable, all differences included in the range ±1 year have to be considered not significant. According to this approach it can be noted from figure 9 that 76% of the observations is included in this range, making age of plantations estimates satisfactorily accurate.

[Figure 9]

Size and economic value of present plantations that were started in the reference period were consequently estimated from the local estimate of the age of plantations as mapped at the previous step. Results are reported in figure 10a and 10b and table 1.

[Figure 10]

It is worth to remind that, results about potential production and economic value must be considered purely indicative. In fact, they can be highly moved from the expected value if unknown plant diseases or unfavorable microsite conditions are present in the area.

[Table 1]

3. Conclusions

MODIS derived EVI time series proved to be effective to map and characterize new oil palm plantations. Detection of new plantations based on local temporal profile analysis revealed to be accurate enough (overall accuracy = 94 %), suggesting that time discriminant is basic in assessing vegetation cover. It also proved to make possible give an approximate estimation of the starting date of new plantations and, consequently, of new productions in the area if a unitary production curve is available. The methodology proposed is useful to different oil palm stakeholder, i.e. local owners and farmers could help to optimize yield , reducing environmental impact and making timely practices in the areas most needy in a precision agriculture contest. Also government authorities or environmental monitoring organizations could use this methodology to detect and assessing agricultural/natural capital and monitoring related environmental and socio-economic impacts. Many limitations, at the moment, still persist: a) detected changes in vegetation cover can be also related to abiotic or biotic disturbance like wildfire, plant diseases, human clear cut. Auxiliary data from other map or institutional source could help to make result more reliable from this point of view; b) production estimates are based on a literature-derived curve of UP. It is not clear if this curve must be better calibrated according to ground data specifically referring to the explored area; c) production estimates are strictly related to the estimate of the date of beginning of plantations. At the moment, the approximation in this estimate in our study area shows 76% of accuracy using Hansen (2013) dataset as reference map. Actually it doesn't know if the persisting error is due to time lag induces by reference method adopted or to our proposed method. Nevertheless, GFC dataset it is currently the only available and reliable one for tropical vegetation change detection d) future experiences trying to apply the same methodology are expected to be based on MOD13Q1 version 6 datasets, since the version 5 is going to be dismissed from LPDAAC.

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MAIN TEXT WORD COUNT: 3741 words; 18 570 characters (spaces excused).

Table 1. Column 1: Estimated age of mapped new plantations. Column 2: Area percentage of new plantations at the ith year in respect of the total. Column 3: Estimated production (Ton FFB yr-1) of the new plantations detected at the ith year. Column 4: Estimated income from the new plantations detected at the ith year.

Class Age	***Area % (Tot OP)***	***Ton FFB yr^{-1} for Class Age***	***Producer Price (M USD tonFFB^{-1})***
18	6.03%	0.63	69.64
17	3.84%	0.40	44.94
16	6.79%	0.72	80.44
15	8.13%	0.87	96.38
14	10.75%	1.15	127.43
13	10.71%	1.16	129.25
12	17.30%	1.90	210.39
11	21.76%	2.38	264.62
10	8.83%	0.98	108.68
9	3.30%	0.37	40.70
8	1.46%	0.16	17.47
7	0.66%	0.07	7.57
6	0.26%	0.02	2.63
5	0.02%	0.0014	0.16
4	0.01%	0.0003	0.03
3	0.13%	0.0031	0.34
2	0.02%	-	-
1	0.005%	-	-
New Plantations	0.01%	-	-
TOT OP	**545394 ha**	**10.82**	**1200.66**

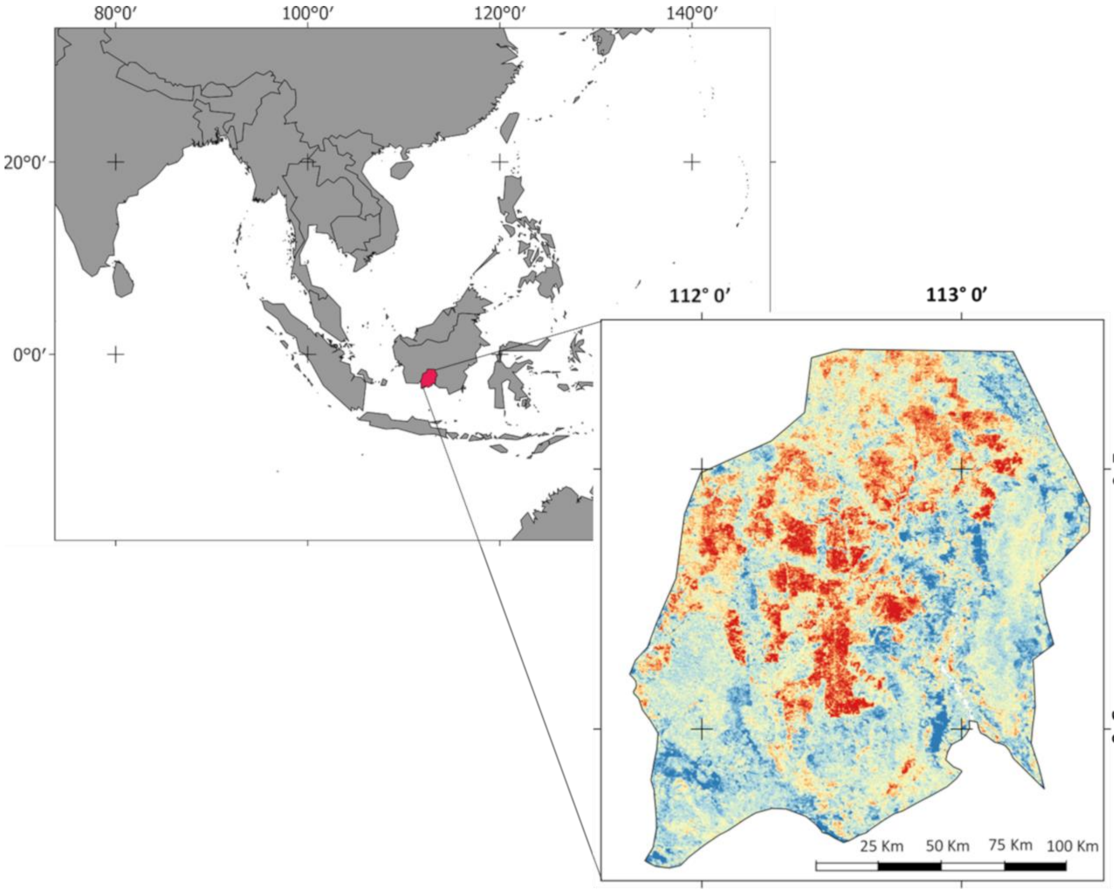
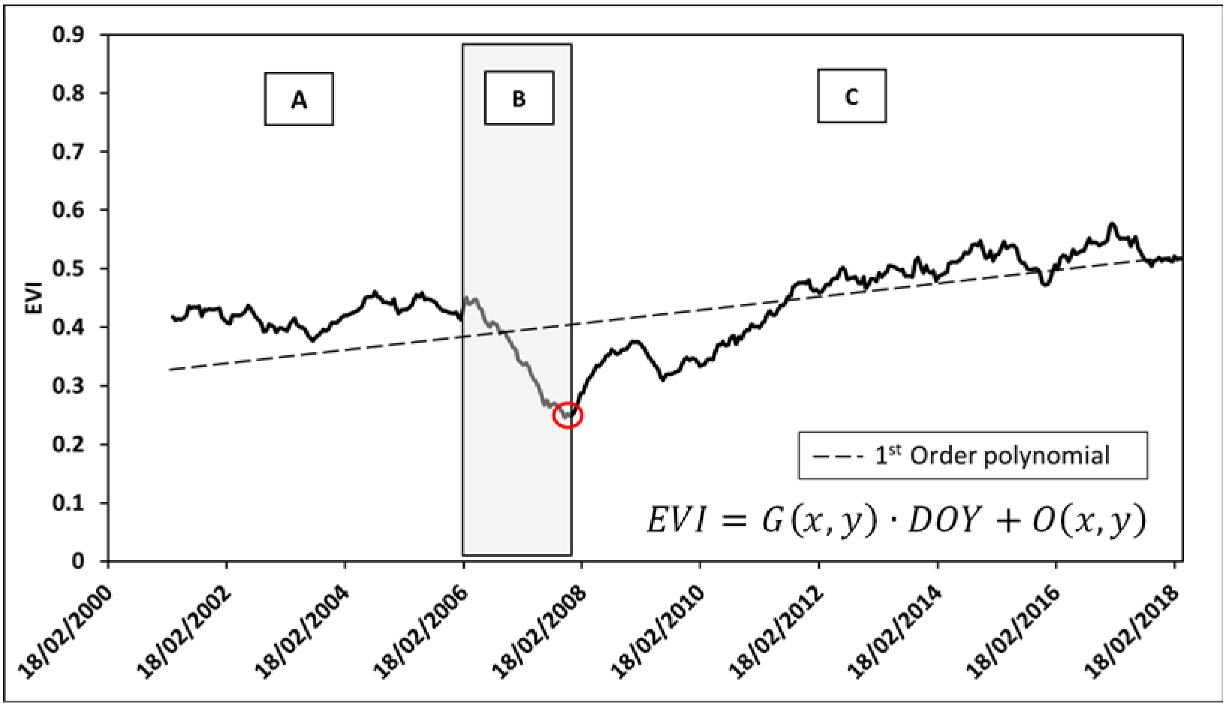


Figure 1 MANCA LA LEGENDA



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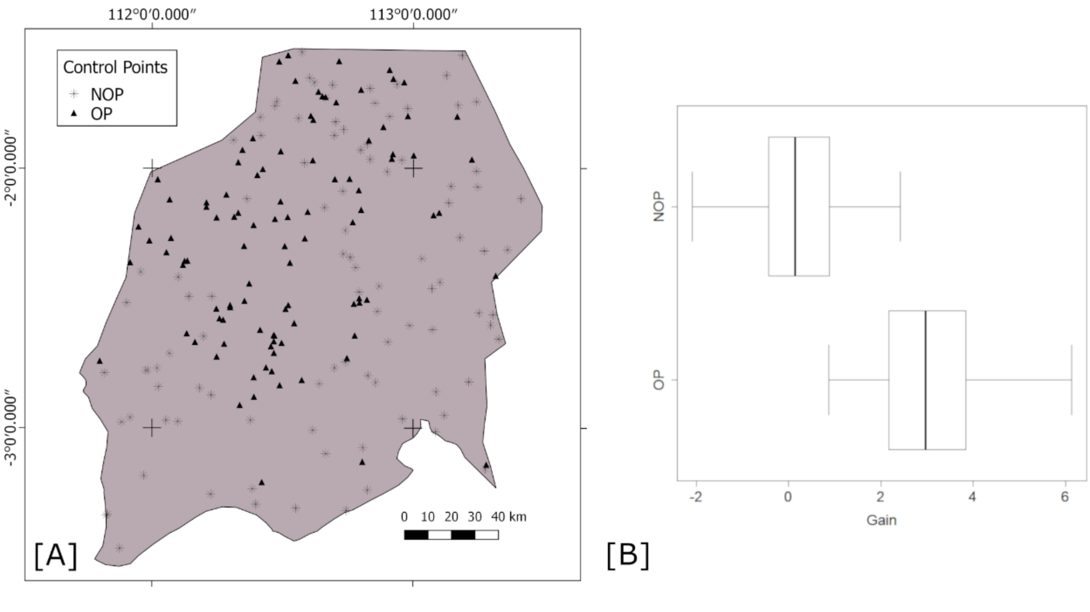
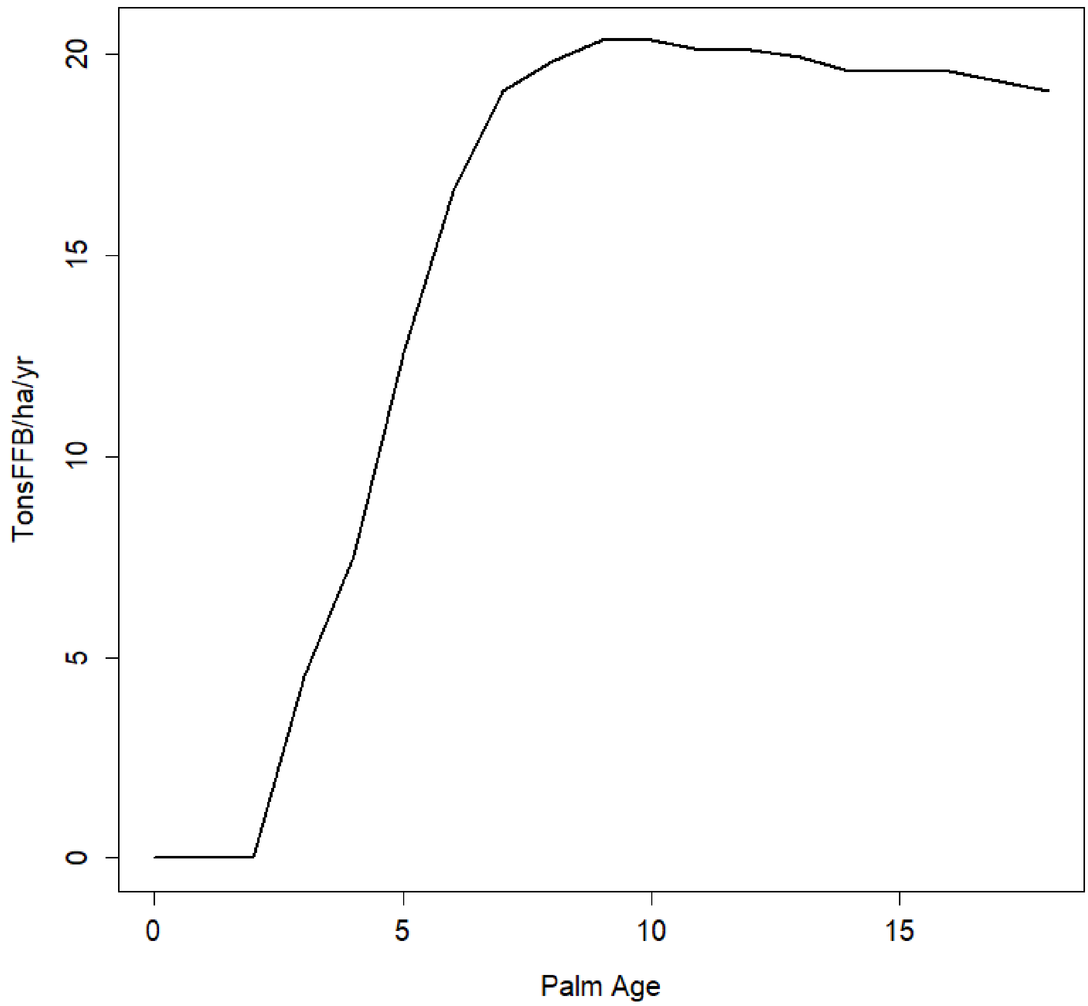


Figure 3

Figure 4



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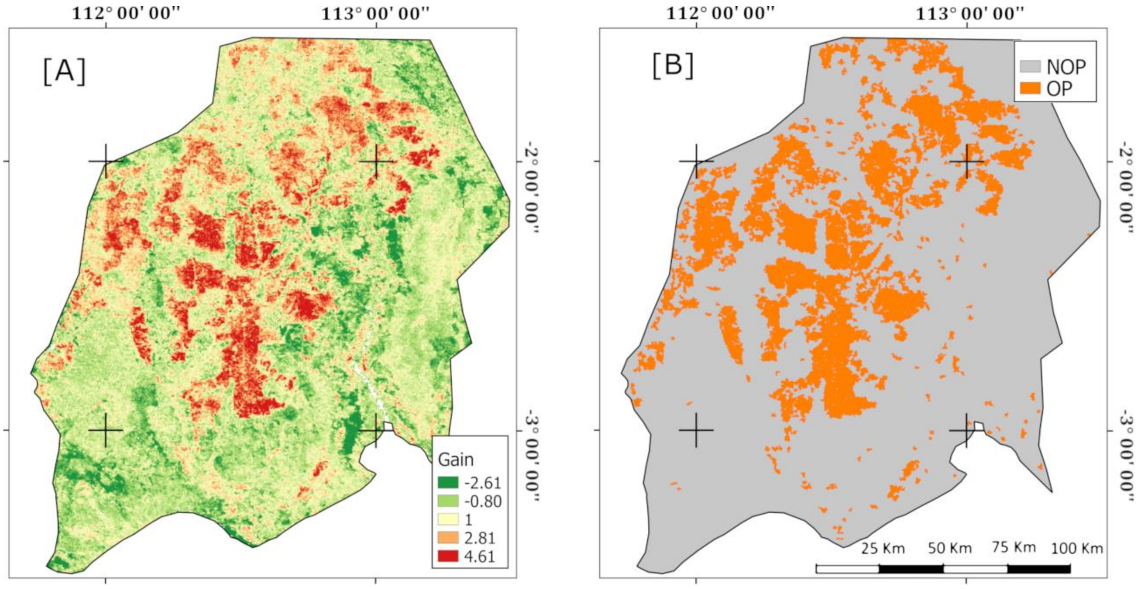

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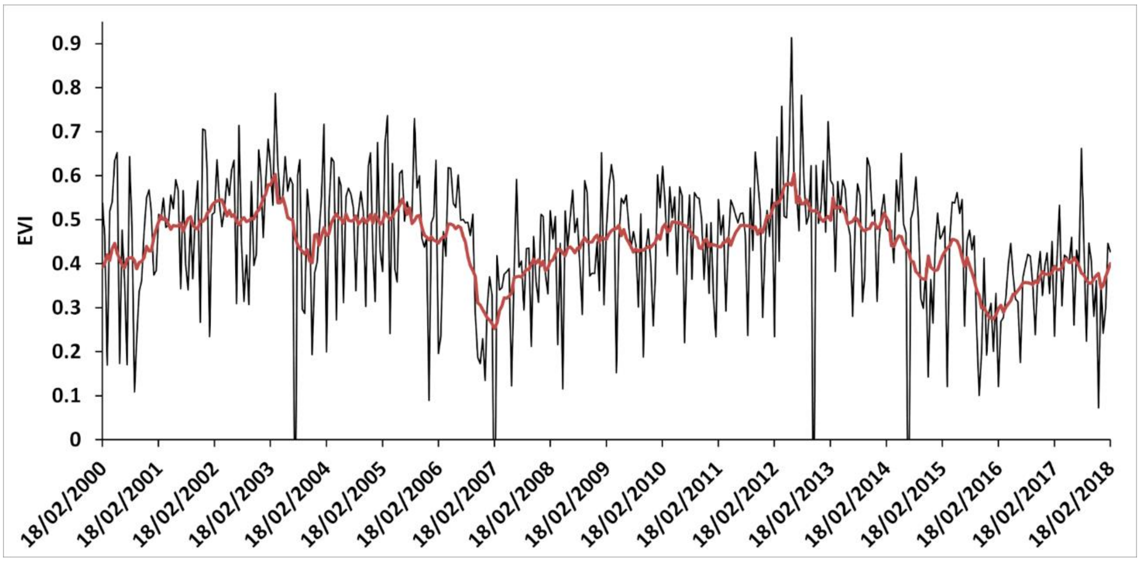

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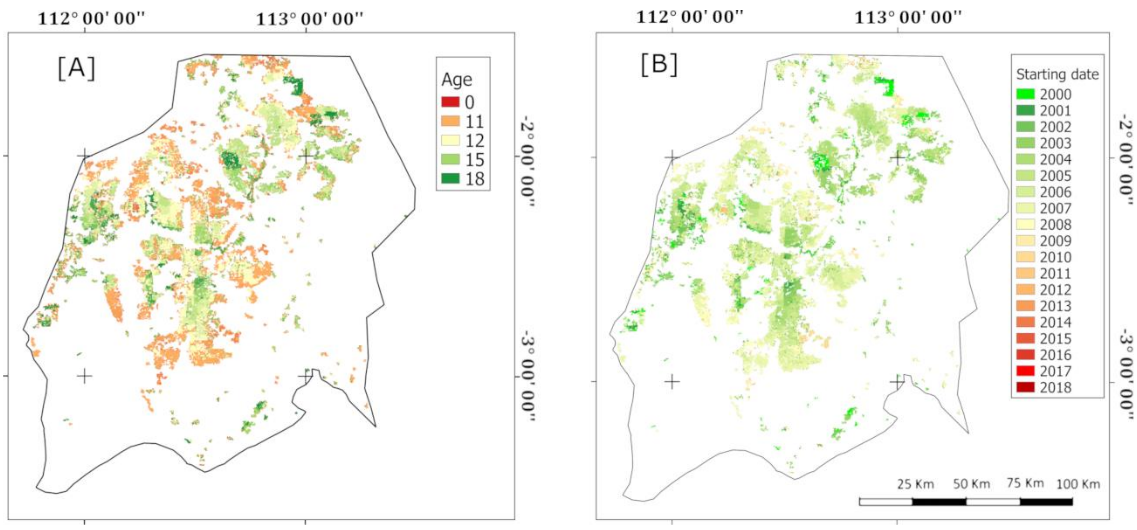
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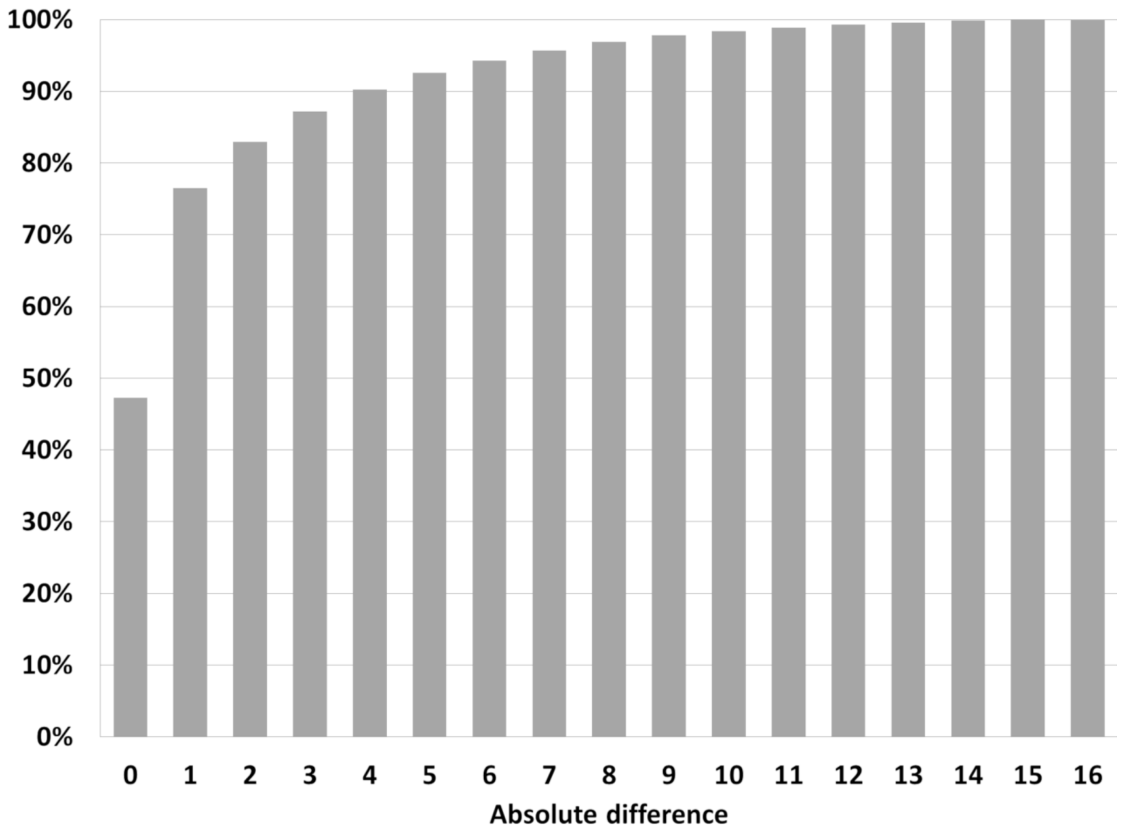
Figure 8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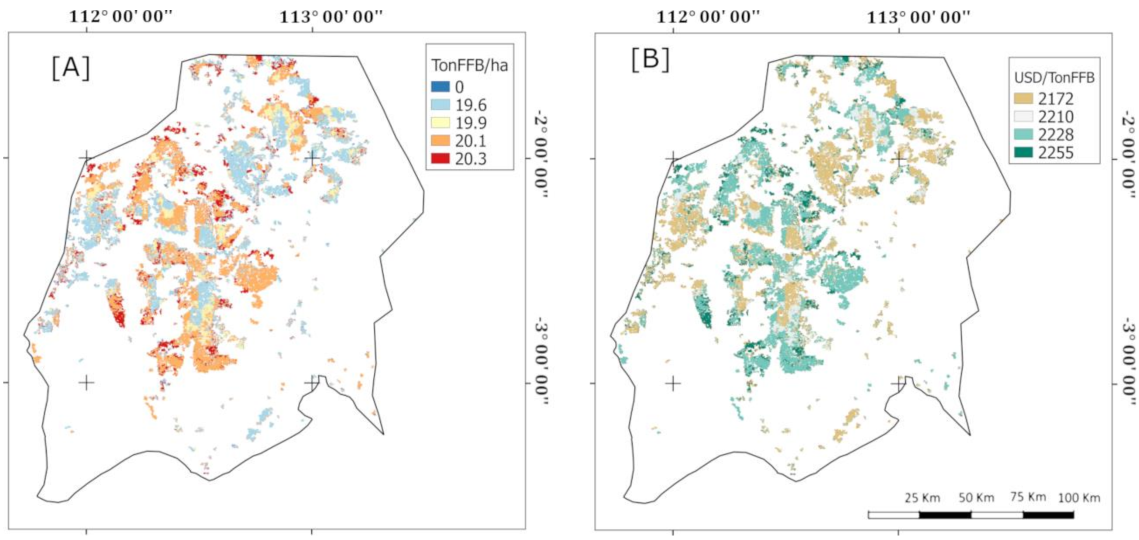
Absolute difference

Figure 9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2210
2228
2255
25 Km
50 Km
75 Km
100 Km

Figure 10

Figure 1. The study area is located in the South of Kalimantan Tengah (Central Kalimantan), a province of Indonesia (Borneo island) (WGS84 reference frame).

Figure 2. Oil palm ETS where the main management phases are indicated: A) previously existing forest cover; B) forest loss; C) palm growing phase. Red circle show the estimated plantation starting date. Dotted line is the 1st order polynomial interpolating the yearly EVI profile of a generic OP pixel, $EVI=G(x,y)\cdot DOY+O(x,y)$. $G(x,y)$ is the local Gain value and $O(x,y)$ the local offset value.

Figure 3. A) Map showing the CPs position in the study area (WGS84 Reference Frame). B) Box plot of CPs gain value for OP and NOP pixels.

Figure 4. Sentinel-2 RGB true colour composite (tile T49MFS, date of acquisition is 2018/02/08). It shows the typical landscape of oil palm plantations where a rectangular pattern of 1000 m x 300 m is the standard management scheme.

Figure 5. Oil palm production curve relating oil unitary production and palms age (Ismail, 2002).

Figure 6. A) Map showing the distribution of the estimated gain value of the 1st order polynomial interpolating the local (pixel) EVI temporal profile; B) Map showing new oil palm plantation started between 2000-2018 (WGS84 Reference Frame) as classified by the proposed algorithm.

Figure 7. EVI temporal profile of a generic OP pixel before (black line) and after (red line) selective filtering.

Figure 8. A) Map of new plantations starting date; B) Map of new plantations age (WGS84 Reference Frame).

Figure 9. Cumulative relative frequencies of absolute differences of transition matrix.

Figure 10. A) LP map (Ton FFB ha^{-1} yr^{-1}); B) Economic value of plantation (USD $tonFFB^{-1}ha^{-1}$) (WGS84 Reference Frame).